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Procedia CIRP 7 (2013) 473 – 478
www.elsevier.com/locate/procedia

Forty Sixth CIRP Conference on Manufacturing Systems 2013

Modelling complex production processes in aerospace industry based on dimensional analysis

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Abstract

This paper looks at the application of the principals of dimensional analysis to identify relations between key parameters of the production system in order to construct a process model that can quantitatively describe the influence of manufacturing process variables, type of technology employed and the material flow on the integral productivity for both batch and flow production architectures of the aerospace production facilities. This process model allows the construction of closed cycle production chains for aerospace parts that form critical path in the assembly sequence of the final product. This approach has been successfully applied to solve the problem of the manufacturing process sequence and material flow optimization for gas-turbine compressor blades production. In conclusion one can say that the developed production process model allows to obtain a numerical assessment of the change in integral productivity as a result of controlled variation in parameters of the manufacturing system which in turn allows to design effective production systems based on optimization of the system parameters.

Selection and peer-review under responsibility of Professor Pedro Filipe do Carmo Cunha

Keywords: Process modelling; dimensional analysis; process optimization; structural optimization; flexible manufacturing

1. Introduction

Manufacturing system of an aerospace factory is a complex layout of different types of production equipment (CNC machining centers, forging/bending presses, welding stations, riveting machines, coordinate measuring machines, assembly jigs, etc) that accommodates both flow and batch production process architectures.

Typical operational conditions of aerospace production facilities can be characterized by long lead times, complex process flow patterns, low batch sizes, tight quality control, high variety of part families, etc.

Traditional approaches to modeling manufacturing systems are based on the usage of Petri nets, graph theory, numerical methods and even network theory. Most of these methodologies can only describe certain narrow elements of the production system (material supply planning, work scheduling, capacity planning, tool supply, etc) and as a result lack the ability to connect manufacturing process parameters with logistical elements of the factory layout.

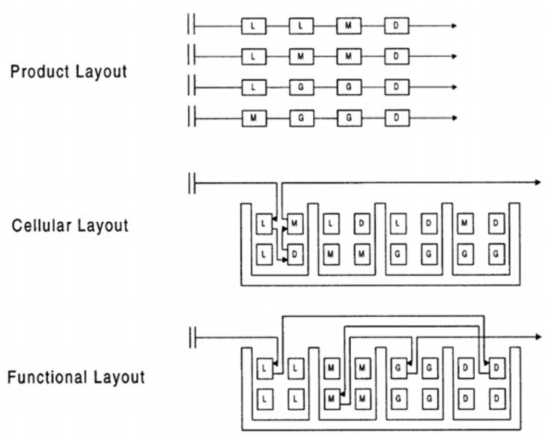

Fig. 1. Traditional types of manufacturing facility layouts (Key: L – lathe, M – mill, G – grinder, D – drill)

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doi:10.1016/j.procir.2013.06.018

In turn the choices of one of the traditional manufacturing facilities layouts of aerospace factories (Fig. 1) are largely based on the planned production volumes and product variety.

Whereas the design requirements of the parts to be made are ensured largely by the order sequence of manufacturing operations as well as the equipment employed at each process step.

On the other hand true optimization of the value creation chain and the facility layout can be achieved through creation of such production process model that combines parameters of the manufacturing processes which are responsible for the changes in shape and properties of the raw material as well as the parameters of the logistical and operational processes that govern the material flow, work in progress levels and production lead times.

2. Traditional production processes modeling approaches

2.1. .Manufacturing process modelling

Modeling and optimization of process parameters of any manufacturing process is usually a difficult task where the following aspects are required: knowledge of manufacturing process, empirical equations to develop realistic constraints, specification of machine capabilities, development of an effective optimization criterion, and knowledge of mathematical and numerical optimization techniques. A human process planner selects proper parameters using his own experience or from the handbooks. Performance of these processes, however, is affected by many factors and a single parameter change will influence the process in a complex way. Because of the many variables and the complex and stochastic nature of the process, achieving the optimal performance, even for a highly skilled operator is rarely possible. An effective way to solve this problem is to discover the relationship between the performance of the process and its controllable input parameters by modeling the process through suitable mathematical techniques and optimization using suitable optimization algorithm [1].

The first necessary step for process parameter optimization is to understand the principles governing the manufacturing process by developing an explicit mathematical model which may be mechanistic and empirical [2]. The model in which the functional relationship between input–output and in-process parameters is determined analytically is called mechanistic model. However, as there is lack of adequate and acceptable mechanistic models for manufacturing processes, the empirical models are generally used in manufacturing processes. The modeling techniques of input–output and in-process parameter relationships are mainly based on statistical regression, fuzzy set theory, and artificial neural networks.

2.2. Logistical process modelling

Logistical processes in an aerospace manufacturing facility play a significant role in providing competitiveness of the production system. Traditional elements of the logistical processes include material flow planning, supply chain control, operations scheduling, equipment capacities balancing, etc.

One way to obtain an estimate the effectiveness of the scheduling is the “in-cycle parallelism” (ICP) indicator which shows the ratio for an order of the sum of its equipment utilization times to its throughput time. This indicator is suitable for use compering orders with uniform processing times with respect to their throughput characteristics.

Logistical system of the shop-floor in a modern aerospace manufacturing facility is a complex interconnection of semi-finished parts, secondary material and information flows (Fig. 2).

Fig. 2. Aerospace facility shop-floor layout

Practical logistical problems often contain nonlinearities, combinatorial relationships and uncertainties that cannot be modelled effectively by simply listing an objective and a collection of constraints in the "approved mathematical programming manner." Many of these complexities can only be captured by resorting to simulation - an outcome that poses grave difficulties for classical optimization methods. In such situations, typically the only recourse available is to itemize a series of scenarios in the hope that at least one will give an acceptable solution. Consequently, a long-standing goal in both the optimization and simulation communities has been to create a way to guide a series of simulations to produce high quality solutions. Such an objective is essential to cope with the fact that many real world production process flow problems are beyond the solution capabilities of traditional mathematical optimization systems [3]. The existing process optimization techniques are largely based on discrete event simulation and are suitable for work scheduling in automated flexible manufacturing systems were production is performed by CNC machining centers [4].

3. General production process model

3.1. Process parameters identification

Generally speaking all production processes in aerospace industry are discrete. However for statistically significant periods of time the processes can be represented by continues variables and parameters.

One way to identify the relationships between process variables of a complex system is to apply the principles of dimensional analysis [5].

In order to identify the key process variables that best describe the production process of an aerospace part a set of performance indicators of a production system is considered.

Productivity (P) – Number of parts produced in a given time period, indicates the throughput of the production system and the lead time of the

Production batch size (V) – Number of identical parts in a production batch.

Quality acceptance level (Q) – Number of parts in a production batch that are made to the specification and do not require rework.

Operational cycle time (T_{cycle}) – Total cycle time of all value added operations in the manufacturing process.

Equipment setup time (T_{setup}) – Total time spent to setup the equipment during change from one part family to another.

Production area (A) – Effective production area of a manufacturing system including transportation and installation area.

Part traveling distance (d) – Total distance travelled by the aerospace part during the manufacturing process between operations.

Work in progress level (W) – Average amount of work in progress including preforms and semi-finished parts in the production system measured in value added time.

Scheduled production loading (S) – Number of parts that have to be manufactured according to the monthly production schedule measured in total production time.

Part preform mass ($M_{preform}$) – Mass of the part preform.

Finished part mass ($M_{finished}$) – Mass of the finished part at the end of the manufacturing process sequence.

Taking the production system throughput (productivity) as the main dependent variable the generalised form of the process relationship can be described by equation (1) as follows:

$$P = f\left(V, Q, T_{cycle}, T_{setup}, A, d, W, S, M_{preform}, M_{finish}\right) \quad (1)$$

3.2. Production process modeling

The analytical expression for quantitative evaluation of the productivity changes is constructed by means of the dimensional analysis methods.

The first step in performing dimensional analysis is to identify dimensions of key process variables both dependent and independent (Table 1).

Table 1. Production process variables (Key: M – mass, L – length, T – time, N – quantity)

Variables	Typical units	Dimensions
Independent variables		
V	piece	N
Q	piece	N
T_{cycle}	hour	T
T_{setup}	hour	T
A	m^2	L^2
d	m	L
W	hour	T
S	hour	T
$M_{preform}$	kg	M
M_{finish}	kg	M
Dependent variable		
P	parts/hour	N/T

The next step in the analysis is to form non-dimensional groups of the variables from Table 1.

Application of the elimination method to the set of variables yields the following set of non-dimensional groups:

Group	$\frac{P \cdot T_{cycle}}{Q}$	depends on	$\frac{S}{W}$	$\frac{Q}{V}$	$\frac{A}{d^2}$	$\frac{M_{finish}}{M_{preform}}$	$\frac{T_{cycle}}{T_{setup}}$
Dimensions	-		-	-	-	-	-

The above result can be written in the form of a process equation (2):

$$\frac{P \cdot T_{cycle}}{Q} = \alpha \cdot \left(\frac{T_{cycle}}{T_{setup}}\right)^{\beta} \cdot \left(\frac{Q}{V}\right)^{\gamma} \cdot \left(\frac{A}{d^2}\right)^{\delta} \cdot \left(\frac{S}{W}\right)^{\theta} \cdot \left(\frac{M_{finish}}{M_{preform}}\right)^{\omega} \quad (2)$$

Where α, β, γ, δ, θ and ω are constants.

Taking the productivity (throughput) as the optimization criterion the process equation becomes equation (3):

$$P = \alpha \cdot \left(\frac{Q}{T_{cycle}}\right) \cdot \left(\frac{T_{cycle}}{T_{setup}}\right)^{\beta} \cdot \left(\frac{Q}{V}\right)^{\gamma} \cdot \left(\frac{A}{d^2}\right)^{\delta} \cdot \left(\frac{S}{W}\right)^{\theta} \cdot \left(\frac{M_{finish}}{M_{preform}}\right)^{\alpha} \quad (3)$$

There are ten independent variables involving four dimensions so Buckingham's rule predicts that there must be at least six dimensionless groups in the final equation. Hence the generalised production process model is adequate in terms of the number of groups present [6].

The integral productivity of the whole production system can be described be equation (4).

$$P_{system} = \sum_{i=1}^{n} P_i \quad (4)$$

Where: n – number of part variants produced in the system,

$$P_i = \alpha \cdot \left(\frac{Q}{T_{cycle}}\right)_i \cdot \left(\frac{T_{cycle}}{T_{setup}}\right)_i^{\beta} \cdot \left(\frac{A}{d^2}\right)_i^{\gamma} \cdot \left(\frac{S}{W}\right)_i^{\delta} \cdot \left(\frac{M_{finish}}{M_{preform}}\right)_i^{\omega}$$

4. Production process optimization based on the process model

4.1. Gas-turbine compressor blade production process model

The generalised production process model described by equation (3) can be applied to any descrete production structure of aerospace parts by means of identifing the values of constants α, β, γ, δ, θ and ω for manufacturing environment of the specific factory.

In order to identify the values of constants α, β, γ, δ, θ and ω for the gas-turbine compressor blades production process a target function is set by equation (5).

$$F(x_i, y_i, z_i, k_i, h_i, g_i, \alpha, \beta, \gamma, \delta, \theta, \omega) = \\ = \sum_{i=1}^{n} P(x_i, y_i, z_i, k_i, h_i, g_i, \alpha, \beta, \gamma, \delta, \theta, \omega) - \sum_{i=1}^{n} P_i \quad (5)$$

Where: P_i – actual productivity value based of the statistical data; x_i – $\left(\frac{Q}{T_{cycle}}\right)_i$; y_i – $\left(\frac{T_{cycle}}{T_{setup}}\right)_i$; z_i – $\left(\frac{Q}{V}\right)_i$; k_i – $\left(\frac{A}{d^2}\right)_i$; h_i – $\left(\frac{S}{W}\right)_i$; g_i – $\left(\frac{M_{finish}}{M_{preform}}\right)_i$;
n – number of known values of productivity.

The values of constants α, β, γ, δ, θ and ω will approach the target if the value of function (5) will be minimum [6].

$$F(x_i, y_i, z_i, k_i, h_i, g_i, \alpha, \beta, \gamma, \delta, \theta, \omega) \rightarrow \min$$

The application of the gradiant method for identification of the target constants values requires the formation of the iteration principle given by variable vector $\boldsymbol{X_{j+1}}$ which is set by equation (6).

$$\boldsymbol{X_{j+1}} = \boldsymbol{X_j} - \boldsymbol{G}(\boldsymbol{X_j}) \quad (6)$$

Where: vector $\boldsymbol{X_j} = (\alpha_i, \beta_i, \gamma_i, \delta_i, \theta_i, \omega_i)$; vector $\boldsymbol{G(X_j)} = \left(\frac{\partial F}{\partial \alpha_j}, \frac{\partial F}{\partial \beta_j}, \frac{\partial F}{\partial \gamma_j}, \frac{\partial F}{\partial \delta_j}, \frac{\partial F}{\partial \theta_j}, \frac{\partial F}{\partial \omega_j}\right)$.

The partial derivatives which form vector $\boldsymbol{G(X_j)}$ are defined as follows by a set of equations (7).

$$
\left.
\begin{aligned}
\frac{\partial F}{\partial \alpha} &= \sum_{i=1}^{n} x_i \cdot y_i^{\beta} \cdot z_i^{\gamma} \cdot k_i^{\delta} \cdot h_i^{\theta} \cdot g_i^{\omega} \\
\frac{\partial F}{\partial \beta} &= \alpha \sum_{i=1}^{n} x_i \cdot y_i^{\beta} \cdot z_i^{\gamma} \cdot k_i^{\delta} \cdot h_i^{\theta} \cdot g_i^{\omega} \cdot \ln y_i \\
\frac{\partial F}{\partial \gamma} &= \alpha \sum_{i=1}^{n} x_i \cdot y_i^{\beta} \cdot z_i^{\gamma} \cdot k_i^{\delta} \cdot h_i^{\theta} \cdot g_i^{\omega} \cdot \ln z_i \\
\frac{\partial F}{\partial \delta} &= \alpha \sum_{i=1}^{n} x_i \cdot y_i^{\beta} \cdot z_i^{\gamma} \cdot k_i^{\delta} \cdot h_i^{\theta} \cdot g_i^{\omega} \cdot \ln k_i \\
\frac{\partial F}{\partial \theta} &= \alpha \sum_{i=1}^{n} x_i \cdot y_i^{\beta} \cdot z_i^{\gamma} \cdot k_i^{\delta} \cdot h_i^{\theta} \cdot g_i^{\omega} \cdot \ln h_i \\
\frac{\partial F}{\partial \omega} &= \alpha \sum_{i=1}^{n} x_i \cdot y_i^{\beta} \cdot z_i^{\gamma} \cdot k_i^{\delta} \cdot h_i^{\theta} \cdot g_i^{\omega} \cdot \ln g_i
\end{aligned}
\right\} \quad (7)
$$

The starting point of the iteration is set by vector $\boldsymbol{X_{j=1}}$ **= (1, 1, 1, 1, 1, 1)** and the iterations are repeated until $\left|(G(X_j)\right| \le 0.05$.

The coresponding target values of constants α, β, γ, δ, θ and ω for the gas-turbine compressor blades production process based on the statistical data which contains actual values of production process parameters and corresponding productivity levels are presented in Table 2.

Table 1. Production process constants values for gas-turbine blades manufacturing

α	β	γ	δ	θ	ω
2.94	0.62	1.37	0.82	0.85	1.24

Hence the relationship that connects the productivity with the key parameters of the gas-turbine compressor blades production process can be represented by equation (8):

$$
P = 2.9 \cdot \left(\frac{Q}{T_{cycle}}\right) \cdot \left(\frac{T_{cycle}}{T_{setup}}\right)^{0.62} \cdot \left(\frac{Q}{V}\right)^{1.37} \cdot \left(\frac{A}{d^2}\right)^{0.82} \cdot \left(\frac{S}{W}\right)^{0.85} \cdot \left(\frac{M_{finish}}{M_{preform}}\right)^{1.24} \quad (8)
$$

The process optimization potential of the derived equation (8) consists in the ability to quantitatively evaluate the changes in production rate caused by controlled variation of process parameters without the need to collect additional experimental data.

4.2. Gas-turbine compressor blade production process optimization

Application of the developed production process model described by equation (8) to the manufacture of gas-turbine compressor blades allowed to optimize the manufacturing process structure and the material flow between the operations with the end result of total production lead time reduction.

In order to achieve an increase in productivity of the compressor blades the preform material volume has been reduced by means of employing the isothermal stamping technology and reducing the stock allowance (Fig. 3).

Fig. 3. Compressor blade preform

The transportation distances of preforms and semi-finished parts have been reduced by creating closed cycle production chains for selected part families which form the bulk of the production volume (Fig. 4).

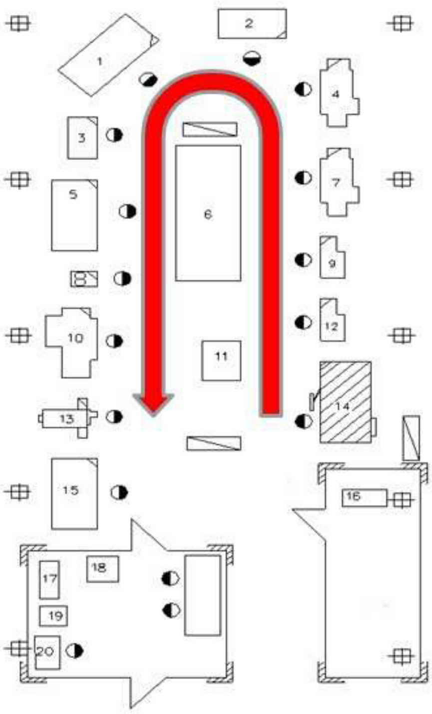

Fig. 4. Optimized manufacturing process flow for compressor blades

Operational cycle times have been reduced by employing automated polishing centres instead of manual polishing of the aerodynamic surfaces of the compressor blade [7].

The equipment setup time inquired during the change of compressor blade types produced has been reduced through the application of modular fixtures with standard attachment mechanisms (Fig. 5).

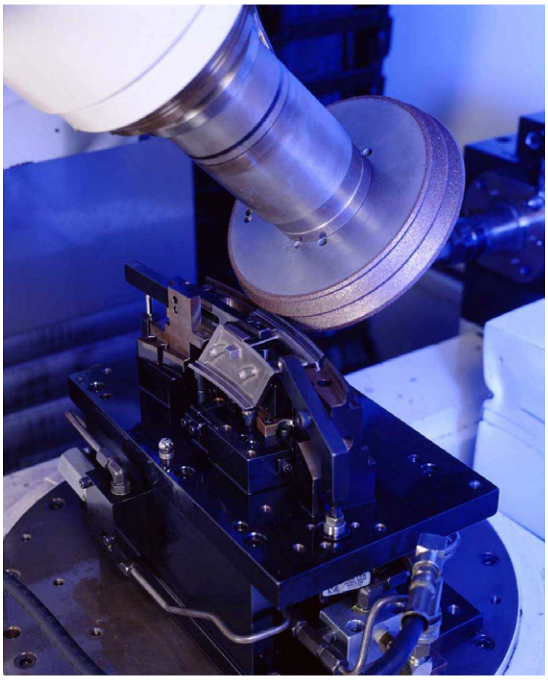

Fig. 5. Modular fixtures for Gas-turbine blades manufacture

Total increase in throughput due to the production process optimization based on the developed process model achieved by changing the key process variables has been accounted to 75% for manufacture of compressor blades at the "Gas-turbine engineering research and production center "SALUT".

The validation of the results obtained by means of the developed process model has been performed by application of petri-net methodology in relation to shop-floor throughput time distribution. The simulation has been performed in the Queuing Event Simulation software package DELMIA QUEST. The boundary conditions for the simulation were set to be the technological capabilities of the production equipment, transfer system and available tooling.

5. Conclusion

Improving the competitiveness of aerospace manufacturing facilities which are characterized by interconnected production chains and complex material flows can be achieved by optimization of key production process parameters that describe the production system itself.

Application of the dimensional analysis has allowed to identify process parameters and form the relationship between key process variables to build a process model that connects manufacturing process parameters with logistical elements of the factory operation which has been successfully applied to increase the throughput of gas-turbine compressor blades at the "Gas-turbine engineering research and production center "SALUT".

The major limitation of the developed methodology is the necessity to collect statistical data which represents the distribution of productivity achieved by different combinations of process parameters, in order to find the corresponding values of constants α, β, γ, δ, θ and ω to be able to construct the required process model.

The next research step in creating a more generalized process model for production of complex aerospace parts is to incorporate subassembly and general assembly operations into the developed methodology.

References

[1] Apple, J. Plant Layout and Material Handling. Wiley, editor. New York: Academic Press; 1977. p. 240.
[2] Grigoriev S, Kutin A. Innovative development of high-tech manufacturing on the basis of computer integrated systems. Automation and modern technologies 2011;11:82-89.
[3] Burbidge J. Production flow analysis. Production Engineer 1971;50:139 -152.
[4] Spur G, Sellinger G. Simulation proceeding-scheduling concept for flexible manufacturing systems. CIRP Annals 1983;32/1:385-388.
[5] Pankhurst R. Dimensional Analysis and Scale Factors. Chapman and Hall; 1985. p. 215.
[6] Duffin S. Optimization theory and applications. Wiley Eastern Limited, New York: Academic Press; 1978. p. 286.
[7] Grigoriev S, Kutin A, Pirogov V. Advanced NC Programming for 5-Axis machining. Procedia CIRP 2012;1:102-107.